

# Winners and Losers of Marketplace Lending: Evidence from Borrower Credit Dynamics

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# Consumer Lending in the United States

- ▶ Consumer lending constitutes significant share of U.S. economy
  - ▶ Accounts for \$3.6 trillion as of 2017
- ▶ Banking intermediaries serve as primary providers of credit to most consumers
  - ▶ Specialize in screening and monitoring, and enjoy economies of scale in reducing information asymmetry (Diamond, 1984; Ramakrishnan and Thakor, 1984)
- ▶ Consumer lending market rife with inefficiencies
  - ▶ Over-reliance on crude, formulaic methods to determine creditworthiness
  - ▶ Significant informational frictions
  - ▶ High interest rates on loans, even for high credit quality applicants (Stango and Zinman, 2009)
  - ▶ Post-crisis capital requirements and regulatory restrictions further limiting credit access

# Rise of FinTech in Consumer Credit Markets

- ▶ Banking inefficiencies creating entry avenues for innovators
  - ▶ Changes in consumer attitudes and technological improvements also possible contributors
- ▶ Marketplace lending (MPL) platforms specializing in peer-to-peer (“P2P”) lending in the consumer credit market
- ▶ Reliant on online marketing and underwriting platforms
  - ▶ Traditional banks not involved in loan origination process
- ▶ Alternative loan pricing schemes

# Features of MPL Platforms

- ▶ Process relies on matching individual borrowers to prospective investor-lenders
  - ▶ Information asymmetry reduced through credit-bureau generated borrower reports made available by MPL
  - ▶ Aids in possibly overcoming the principal-agent problem (Jensen and Meckling, 1976)
- ▶ Disbursed MPL funds are unsecured
  - ▶ MPL platform plays role of broker; lenders bear full risk of borrower defaults
- ▶ MPL loans used primarily for debt consolidation
  - ▶ Over 70% of loan applicants on MPL platforms in US state “expensive debt consolidation” as primary reason for requiring MPL funds (source: Prosper and Lending Club)
- ▶ No mechanism in place to ensure that borrowed MPL funds are used towards reasons stated on loan applications

# Research Questions

- ▶ **Question 1:** Is stated aim of debt consolidation misreported on MPL loan applications?
  - ▶ MPLs lack enforcement mechanisms
- ▶ **Question 2:** Does borrowing from MPLs alter credit profile characteristics?
  - ▶ Default rates, credit card utilization, credit scores, etc.
- ▶ **Question 3:** Identify winners and losers of MPLs
  - ▶ Cross-sectional analysis
  - ▶ Identify mechanisms that determine benefits or costs imposed on MPL borrowers
  - ▶ Facilitated by cohort-level analysis comparing borrowers to non-borrowers

# Preview of Findings

- ▶ Credit card balances decline 47% in the quarter of MPL loan origination, before reversing trend
- ▶ Average credit score jumps by approximately 19 points in the quarter of MPL loan origination
- ▶ Findings suggest that credit card limits increase in months following MPL loan origination, especially for subprime borrowers
- ▶ Credit card default rates spike, especially for subprime MPL borrowers
- ▶ Evidence suggests that bank lending actions are triggered by MPL-induced improvement in borrowers' credit scores

# Related Literature

- ▶ Lending decisions within online platforms:
  - ▶ Freedman and Jin (2011), Lin et al. (2013), Iyer et al. (2015), Hildebrand et al. (2016)
- ▶ Determinants of interest rates on MPL loans:
  - ▶ Race and age (Pope and Sydnor, 2011); gender (Barasinska, 2011; Pope and Sydnor, 2011); beauty (Ravina, 2012); stereotypes (Hasan et al., 2018); non-verifiable disclosures (Michels, 2012); group leader bids (Hildebrand et al., 2016)
- ▶ Credit expansion vs. credit substitution?
  - ▶ Jagtiani and Lemieux (2017), Wolfe and Yoo (2018), Buchak et al. (2017)
- ▶ Impact of MPL credit on consumers:
  - ▶ Balyuk (2018), Demyanyk et al. (2017)
- ▶ Importance of credit scores in bank-lending relationships:
  - ▶ Keys et al. (2010), Rajan et al. (2015), Agarwal et al. (2018), Liberman et al. (2017)

# Data Sources

- ▶ Credit bureau trades file:
  - ▶ Information on the various trades opened by an individual (auto, mortgage, student loans, bankcard, etc.)
  - ▶ Used to identify individuals who have borrowed through fintech lenders
- ▶ Credit bureau credit file:
  - ▶ Balance information at monthly frequency for various kinds of trade lines
  - ▶ Monthly utilization ratios
  - ▶ Monthly credit scores
- ▶ Demographic file:
  - ▶ Occupation
  - ▶ Education status
  - ▶ Income



# MPL Borrowers v. Average U.S. Population

	MPL Borrowers	National	Homeowners
<b><u>Panel A: Credit Characteristics</u></b>			
# Open Trades	10.49	4.68	7.58
# Auto Trades	1.02	0.66	0.84
# Mortgage Trades	0.86	0.79	1.07
# Student Loan Trades	2.23	1.66	1.49
# Credit Card Trades	3.84	1.97	2.74
Vantage Score	656.44	675.47	733.84
Total Balance	\$232,463	\$208,195	\$310,142
Auto Balance	\$20,659	\$17,038	\$20,648
Mortgage Balance	\$189,597	\$186,237	\$274,244
Student Loan Balance	\$24,425	\$19,122	\$20,210
Credit Card Balance	\$9,821	\$4,197	\$5,994
Credit Card Utilization	69.42%	30.89%	28.55%
<b><u>Panel B: Income Characteristics</u></b>			
Monthly Income	\$3,602	\$3,437	\$5,232
Debt-to-Income	41.03%	27.82%	45.39%

# Empirical Approach

- ▶ Examine how MPL loans change credit profiles of borrowers
- ▶ Utilize event study methodology similar to Agarwal et al. (2016), and Agarwal et al. (2017):

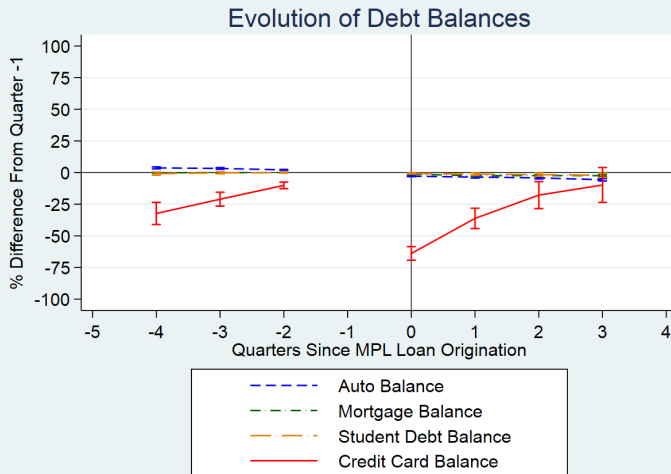
$$\ln(Y_{i,t}) = \sum_{\tau \neq -1} \beta_{\tau} Quarter_{i,\tau} + \gamma \mathbf{X}_{i,t} + \alpha_i + \delta_t + \epsilon_{i,t} \quad (1)$$

- ▶ Definitions:
  - ▶  $Quarter_{-1}$  ( $Quarter_{+1}$ ) refers to months  $[-3,-1]$  (months  $[+4,+6]$ ) in relation to month of MPL loan origination
  - ▶  $\tau$  varies from -4 to +3, with  $\tau = -1$  omitted
  - ▶ Individual- and year-quarter fixed effects
  - ▶ SEs double clustered at individual- and year-quarter levels
  - ▶  $\mathbf{X}_{i,t}$ : Monthly income, educational attainment, occupation, and homeownership status

# Question #1: What type of debt is consolidated?

- ▶ Possible strategic misreporting due to non-verifiable nature of reasons stated on MPL loan applications
  - ▶ Moreover, non-verifiable reasons affect loan pricing on MPL platforms (Michels, 2012)
- ▶ What kind of debt is consolidated?
  - ▶ Comparison of average interest rates:
    - ▶ Auto (4.21% on 60 month loans)
    - ▶ Mortgage (4.125% for 15-year FRM, 3.875% on 5/1 ARM)
    - ▶ Student loans (4.5–7%)
    - ▶ Credit cards (15–20%)
  - ▶ Inefficient consolidation can leave borrowers worse off

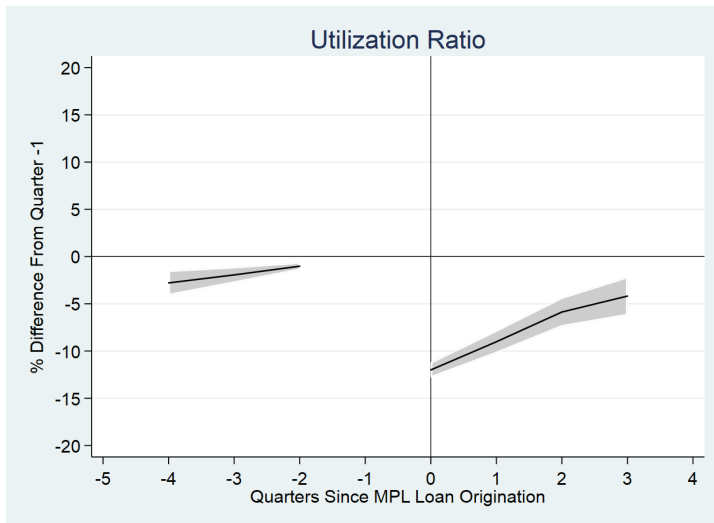
# Evolution of Debt Balances



## Question #2: Long-run effects on credit profile?

- ▶ Are other credit profile characteristics affected by MPL loan-induced credit card debt consolidation?
- ▶ How long do these credit profile changes persist?

# Credit Card Utilization

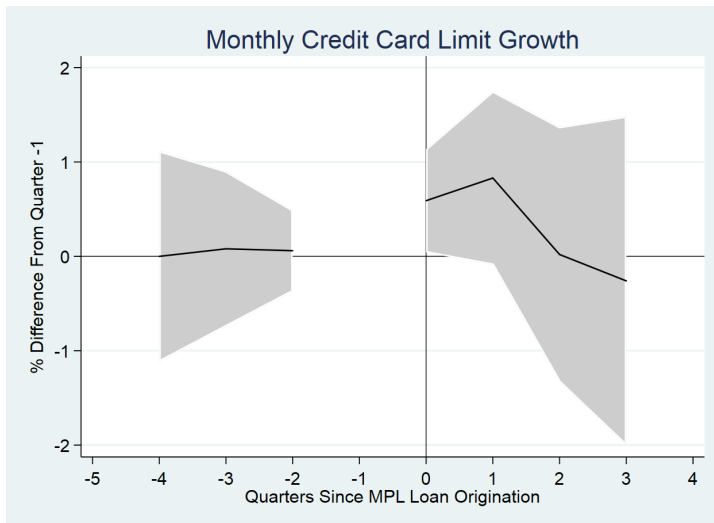


# Determinants of Utilization

$$Utilization = \frac{Balance}{Limit}$$

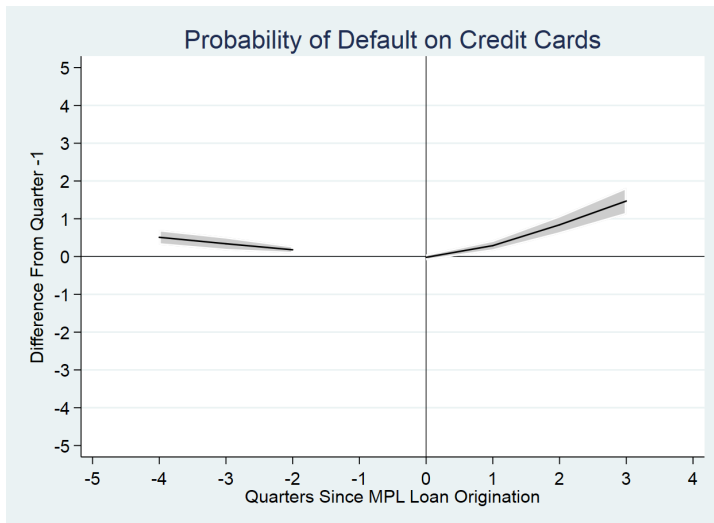
- ▶ Our findings indicate that at the 1-year mark following MPL loan origination:
  - ▶ Balance  $\approx$
  - ▶ Utilization  $\downarrow$
  - ▶ Suggests that: Limits  $\uparrow$

## Long-Run Effects on Credit Profile

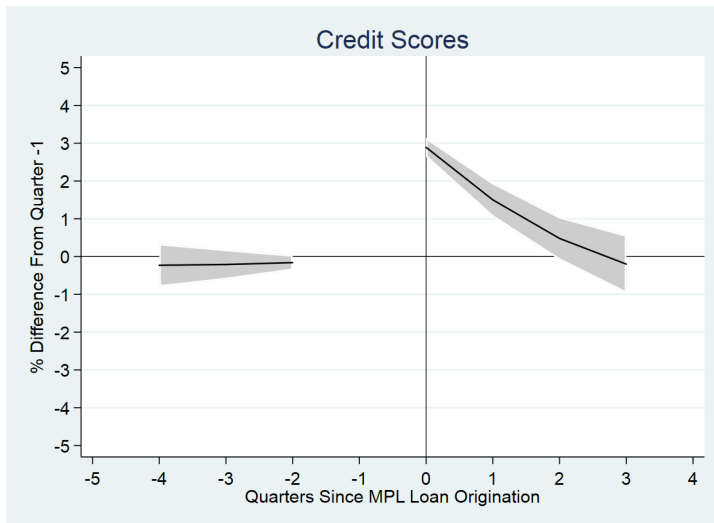
 $\Delta$ (Monthly Credit Card Limits)



# $\mathbb{P}$ (Credit Card Default)



# Credit Scores



# Alternative Channels?

- ▶ Job/Income loss
  - ▶ Results cannot be explained by change in employment or income of the MPL borrower
- ▶ Regional economic factors
  - ▶ Pattern of findings not driven by region-specific shocks exogenous to the MPL borrowers
  - ▶ Robust to 5-digit ZIP  $\times$  Year-Quarter fixed effects

# Identification – Matched-Sample Analysis

- ▶ Creating cohorts of borrowers and non-borrowers:
  - ▶ Identify non-MPL borrowers from same 5-digit (or 9-digit) ZIP as MPL borrower
  - ▶ Identify subset of non-MPL borrowing neighbors with need for credit
  - ▶ Identify neighbors with identical ex-ante credit and income profile trends in calendar time
  - ▶ Use kNN algorithm to identify most similar neighbor to MPL borrower
- ▶ Successful in identifying cohorts of borrowers and neighbors with similar dynamics in credit scores, utilization, debt balances, etc.
- ▶ Results robust to matched-sample analysis
- ▶ Lingering concerns of selection on observables

# Identification – Natural Experiments

- ▶ Identifying ‘shocks’ to geographic regions that could affect MPL share:
  - ▶ Changes in broadband access
  - ▶ Rollout of Google Fiber (used in Fuster et al. (2018))
  - ▶ Bank branch closures
- ▶ Currently ongoing

Who wins or loses from borrowing from MPLs?

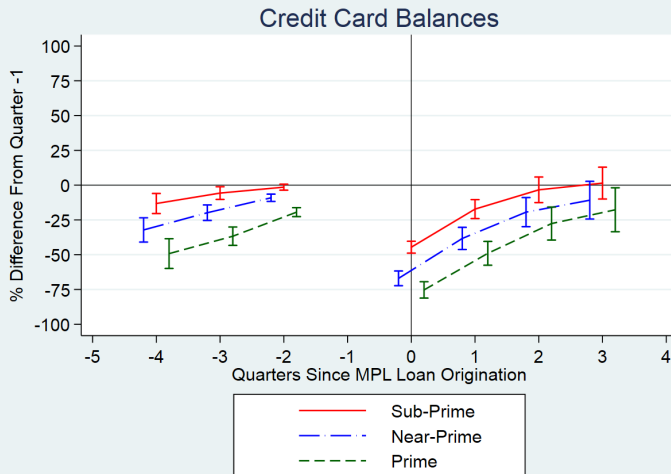
## Differential Patterns based on Credit Status

- ▶ Analysis thus far assumes that all MPL borrowers are of equal sophistication
- ▶ MPL borrowers differ on financial sophistication, however
- ▶ Sophistication proxied through credit score in the month prior to MPL loan origination:

Sophistication Level	Score Range Pre-MPL Origination	Percentage of Total Sample
Subprime	[300, 620)	23%
Near-Prime	[620, 680)	50%
Prime	[680, 850]	27%

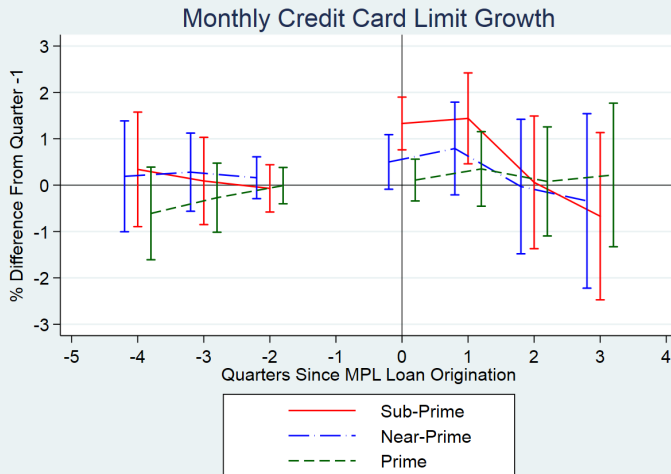
Who wins or loses from borrowing from MPLs?

# Credit Status Cuts – Credit Card Balances



Who wins or loses from borrowing from MPLs?

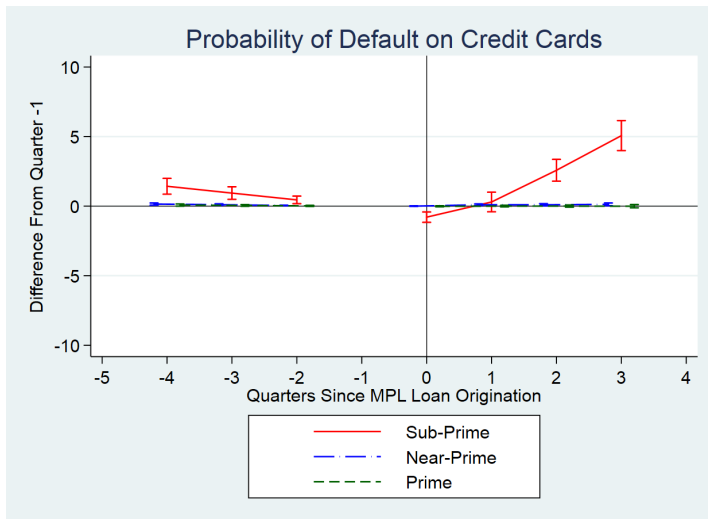
# Credit Status Cuts – $\Delta$ (Credit Card Limits)





Who wins or loses from borrowing from MPLs?

# Credit Status Cuts – $\mathbb{P}(\text{Credit Card Default})$



Do MPLs alter the perceived creditworthiness of borrowers?

# Improvement in MPL Borrower Creditworthiness?

- ▶ Earlier findings suggest that MPL borrowers experience increase in average credit scores in quarter of MPL loan origination
  - ▶ Scores increase by 2.89% ( $\approx 19$  points) for entire sample
- ▶ Findings also show that MPL borrowers experience stronger credit card limit growth immediately following origination
- ▶ Are increases in credit card limits caused by MPL-induced improvement in credit scores?
  - ▶ Studied through cohort-level analysis

Do MPLs alter the perceived creditworthiness of borrowers?

# Empirical Specification

- ▶ Use kNN algorithm to match MPL borrowers to non-borrowing neighbors in same 5-digit (or 9-digit) ZIP with identical ex ante credit and income dynamics
- ▶ Specification relies on comparing borrowers to non-borrowers *within* cohort:

$$\log \left( \frac{\text{AvgScore}_{[+1,+3]}}{\text{AvgScore}_{[-3,-1]}} \right) = \text{MPL\_Borrower}_{i,c} + \gamma \mathbf{X}_{i,c} + \alpha_c + \epsilon_{i,c} \quad (2)$$

- ▶ Instrumental variables setup:

$$\log \left( \frac{\text{AvgCCLimits}_{[+1,+3]}}{\text{AvgCCLimits}_{[-3,-1]}} \right) = \log \left( \frac{\text{AvgScore}_{[+1,+3]}}{\text{AvgScore}_{[-3,-1]}} \right) + \gamma \mathbf{X}_{i,c} \quad (3)$$

$$+ \alpha_c + \epsilon_{i,c}$$

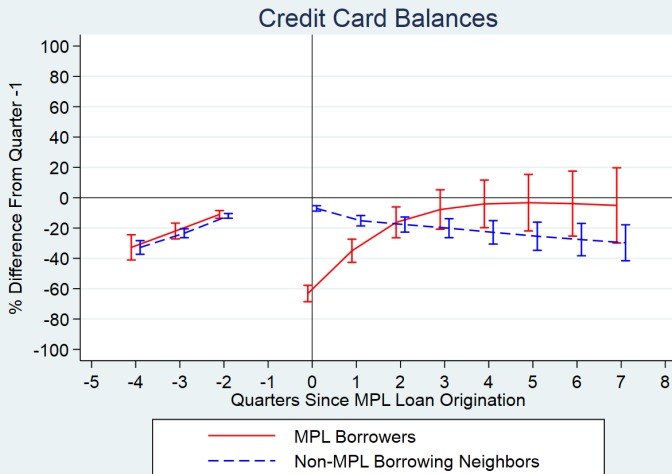
# Impact of MPL Loans on Subprime Borrower Creditworthiness

### ► Near-Prime Cohorts

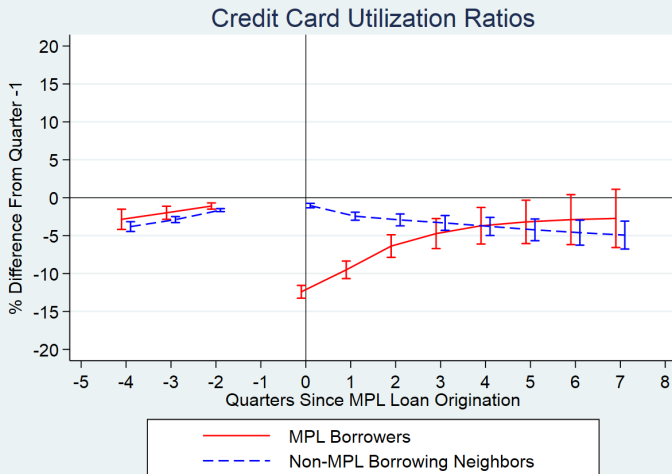
# Conclusion

- ▶ Using credit bureau data, we analyze the credit profile evolution of borrowers on a major U.S. MPL
- ▶ Borrowers use funds to consolidate expensive credit card debt
  - ▶ Lowers credit utilization ratios, elevates credit scores
  - ▶ Consolidation phase is short-lived
  - ▶ Induces increased credit card limits from traditional banks
  - ▶ Significant increases in credit card default rates, especially for subprime MPL borrowers
- ▶ Results indicate that MPL-induced improvements in credit scores trigger bank lending actions
- ▶ Paper highlights how cascading of information between MPL platforms and banks through credit scores can leave some borrowers worse off

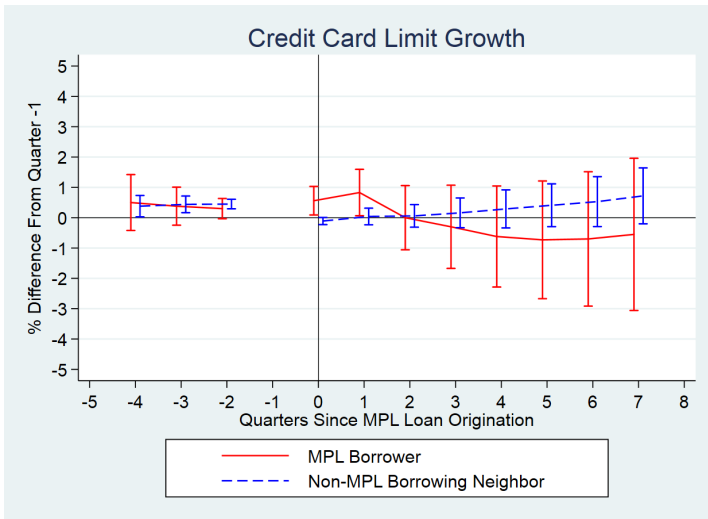
# Matched Sample Comparison – Credit Card Balances



# Matched Sample Comparison – Credit Card Utilization



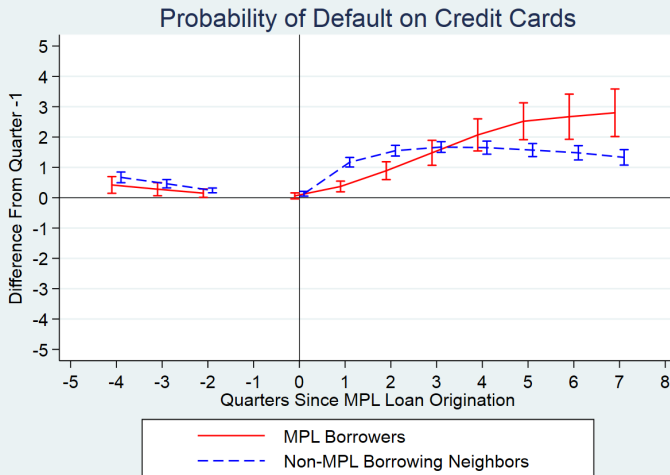
# Matched Sample Comparison – Credit Card Limit Growth



Tables: [5-Digit ZIP](#) [9-Digit ZIP](#), Back: [Back](#)

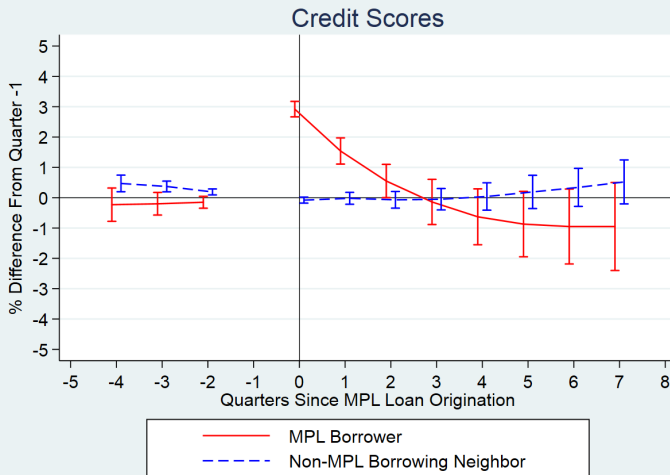


# Matched Sample Comparison – $\mathbb{P}(\text{Credit Card Default})$



Tables: [5-Digit ZIP](#) [9-Digit ZIP](#), Back: [Back](#)

# Matched Sample Comparison – Credit Scores



Tables: [► 5-Digit ZIP](#) [► 9-Digit ZIP](#), Back: [► Back](#)

# Impact of MPL Loans on Near-Prime Borrower Creditworthiness

	1st Stage	IV	OLS	
	$\Delta(\text{Score})$	$\Delta(\text{CC Limits})$	$\Delta(\text{CC Limits})$	$\mathbb{I}(\text{Score}_{\text{post}} \geq 680)$
MPL Borrower	4.25*** (0.04)			32.70*** (0.31)
$\Delta(\text{Score})$		0.11*** (0.01)	0.05*** (0.02)	
Observations	523674	523674	523674	523674
Adjusted $R^2$	0.13	0.01	0.03	0.17
Fixed Effects	C	C	C	C
Controls	✓	✓	✓	✓
F-Stat (Excl Instr.)		11600		

► Back